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An Adapted Gaussian Mixture Model Approach to Accelerometry-Based Movement Classification Using Time-Domain Features

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Abstract— **The accurate classification of everyday movements from accelerometry data will provide a significant step towards the development of effective ambulatory monitoring systems for falls detection and prediction. The search continues for optimal front-end processing methods for use in accelerometry systems. Here, we propose a novel set of time domain features, which achieve a mean accuracy of 91.3% in distinguishing between three postures (sitting, standing and lying) and five movements (sit-to-stand, stand-to-sit, lie-to-stand, stand-to-lie and walking). This is a 39.2% relative improvement in error rate over more commonly used frequency based features. A method for adapting Gaussian Mixture Models to compensate for the problem of limited user-specific training data is also proposed and investigated. The method, which uses Bayesian adaptation, was found to improve classification performance for time domain features, offering a mean relative improvement of 20.2% over a non subject-specific system and 4.5% over a system trained using subject specific data only.**

I. Introduction

The population of the world is aging. The United Nations predicts that by 2100, 28.1% of the world population will be aged 65 years or older compared to 10.0% in 2000 and 6.9% in 1900 [1]. With this aging population comes an increased demand for aged care services. One such area of demand is in falls management and prevention, with falls accounting for approximately half of all injury-related hospital admissions in the over 65 age group [2].

Accelerometry has been proposed as a practical, inexpensive and reliable method for monitoring ambulatory motion in elderly subjects for the detection and prediction of falls. [3]. Robust classification of motions and postures from accelerometry data should allow the development of more reliable methods for monitoring long term change in physiological indicators such as parameters of gait, balance, energy expenditure and general well-being.

Most previous studies on the use of accelerometry in ambulatory monitoring have used multiple accelerometers fixed to specific places on the body, usually a subset of the thighs, wrists, arms, sternum, waist and lower legs [4-6]. A smaller number of studies have investigated the use of a single accelerometry device attached at the waist, sternum or back [7, 8]. Whereas the use of a larger number of accelerometers is likely to provide a higher accuracy in terms of classifying motions and postures, such a system is also likely to be too cumbersome and inconvenient to be truly feasible for long-term ambulatory monitoring.

Previous research into movement classification from accelerometry data has varied widely, incorporating a range of classification methodologies, including rule-based Heuristic methods [8], decision trees, nearest neighbor and Naïve Bayes [7],[4], support vector machines (SVM) [7], neural networks [9], Gaussian Mixture Models (GMMs) and Markov chains [10]. Minimal experimentation has been performed to find the optimal front-end features for these methods. Most studies have used frequency derived features employing an FFT or parameters calculated over long time-windows such as averages or correlations [7, 10].

In this paper, a GMM-based activity classification system is implemented using data from a single, waist-mounted triaxial accelerometer. A novel set of time-domain features are proposed which offer reduced computational complexity and the potential to better detect short-duration, non-periodic movements such as transitions between sitting and standing and taking a couple of steps. These new features are compared with more commonly used frequency domain features in distinguishing between three postures (sitting, standing and lying) and five motions (Stand-to-Sit Transition, Sit-to-Stand Transition, Stand-to-Lie transition, Lie-to-Stand Transition and Walking).

A method for adapting the GMMs to a particular person or device is also proposed. Based on a similar method commonly used in speaker verification [11], this method allows models pre-trained on data from multiple subjects, to be adjusted to better fit a particular person or device, using only a small amount of data from that person or device.

II. Method

A. Device Specifications

The device (Fig. 1) used in these studies is a single, waist-mounted tri-axial accelerometer identical to that in [12]. Two ADXL210 biaxial accelerometers were mounted orthogonally within a pager case measuring 71x50x18 mm. The whole device weighs approximately 50 g including a single AA 1.5 V battery, a wireless transmitter and an

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emergency push button. The data from the waist-mounted device is transmitted over a 433.92 MHz wireless link to a personal computer where the data is stored and further processing is carried out. The resultant sampling rate per channel after transmission is approximately 45 Hz.

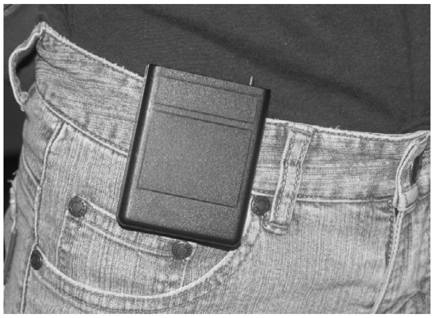

Fig. 1. The single triaxial accelerometry device is attached at the waist and communicates with a PC over wireless.

The device is capable of measuring both static and dynamic accelerations. Thus the signal is the net result of the body acceleration due to movement of the subject, acceleration due to gravity, acceleration due to other external forces and noise.

B. *Data Collection*

The data for these experiments were gathered in an unsupervised pilot study in which six healthy, elderly subjects (4 women, 2 men aged 80-86 years) living independently at home, wore the device each day for a period of 2-3 months. See [13] for further details.

The data used in these experiments were collected during a short routine performed daily by the subjects. The routine involved a directed sequence of the following 11 activities mediated by instructions from the computer and by the person pressing a button on the device when non-timed motions were completed:

1.	Stand (30 seconds)	2.	Sit-down
3.	Sit (10 seconds)	4.	Stand-up
5.	Stand (10 seconds)	6.	Walk
7.	Stand (10 seconds)	8.	Lie-down
9.	Lie (10 seconds)	10.	Stand-up
11.	Stand (10 seconds)		

The collected data were manually checked to ensure that the expected movements were performed, and then segmented to extract data for each of the eight classifications: Standing, Sitting, Lying, Stand-to-Sit Transition, Sit-to-Stand Transition, Stand-to-Lie Transition, Lie-to-Stand Transition and Walking. Between 40 and 100 iterations of each action were collected for each of the six subjects over the 3 month period resulting in over 340 instances of each of the 8 classifications. Each subject's data were divided randomly into training and testing sets in a roughly 60-40% split.

C. *Feature Extraction*

Most accelerometry studies to date have used frequency derived features employing an FFT or parameters such as averages or correlations calculated over long time-windows [7, 10]. In these experiments, we compare one such FFT-based frequency domain method with a novel time-domain parameterization technique.

FFT-based Frequency-Domain Features

FFT-based frequency domain features were proposed in [14] for classification of shiver motion and extended to general activity classification by the same researchers [10]. According to this method [14], data from the three spatial axes is combined into a single magnitude vector and windowed using a 64 sample Hanning window with 50% overlap. A FFT is then taken for each frame to give a 32-dimensional feature vector.

A variety of different combinations of these features were tested by the current authors using a variety of window types and lengths. The most successful version used a simple rectangular window of length 16, calculated the frequency information from each spatial axis separately (rather than combined as a magnitude), and separated the body acceleration and gravity components of the signals prior to the other calculations (using an 8th order elliptic low pass filter with a cut-off frequency of ~0.25 Hz). This resulted in a 48 dimensional feature vector, calculated once every 8 samples as shown in Fig. 2.

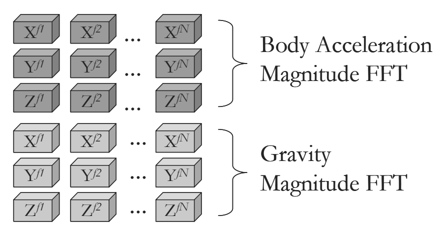

Fig. 2. Block diagram of the selected FFT-based feature vector for one frame of accelerometry data.

Time-Domain Features

A block diagram of the proposed time-domain features is given in Fig. 3. These features model the time-variant nature of the accelerometry waveforms using time derivative components rather than frequency information.

The gravity and body acceleration components of the accelerometry signals were separated using the same low pass filter as in section 2.3.1. These were then concatenated together with:

- A commonly used energy measure – the Signal Magnitude Area [13].
- The first order time derivative of the gravity components, calculated according to

$$\Delta g(t) = \frac{\sum_{d=-D}^{D} d\, g(t+d)}{\sum_{d=-D}^{D} d^2}$$

where *g(t)* is the gravity vector at time t and *D*=2.

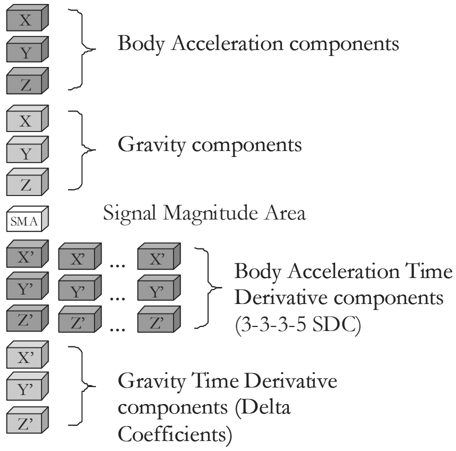

Fig. 3. Block diagram of the proposed time domain feature vector for one frame of accelerometry data.

- A more extensive time derivative sampling known as the Shifted Delta Coefficients. Commonly used in spoken language identification [15], these are calculated from the body acceleration components according to the concatenation of $\Delta b(t+iP)$ for all $0 \leq i < K$, where

$$\Delta b(t+iP) = \frac{\sum_{d=-D}^{D} d\, b(t+iP+d)}{\sum_{d=-D}^{D} d^2},$$

$b(t)$ is the body acceleration vector at time t. D=3, P=3 and K=5.

The resultant 25-dimensional feature vector is calculated at every sample, but requires less computation than the frequency based features described previously. Given that these features do not require long windowed calculations, they could potentially offer improved time-domain resolution for the effective identification and time-localization of short duration and non-periodic movements.

D. Classification

The back-end classification was performed using 32-mixture GMMs. A separate GMM was trained for each movement type using the Expectation Maximization (EM) algorithm applied to the specified training data. For an unknown sequence of data, the correct movement was then selected according to the GMM that gave the highest likelihood score.

E. Subject Specific Adaptation

In order to deploy an effective ambulatory monitoring system one needs to address the problem of gathering adequately representative data. If the system is trained on data from the recipient only, it is likely to be under-trained and therefore insufficiently robust to movement variation. Whereas, if the system is pre-trained on a larger set of data, taken from multiple people, the models may not be specific enough to that person for accurate classification. Due to the computational complexity of the EM algorithm, it is likely to be impractical to retrain the whole system using recipient specific data combined with a full set of general data.

To address this problem, it is proposed that the pre-trained GMMs be adapted to the intended subject using the simpler Bayesian adaptation algorithm. A diagram of the proposed method is given in Fig. 4.

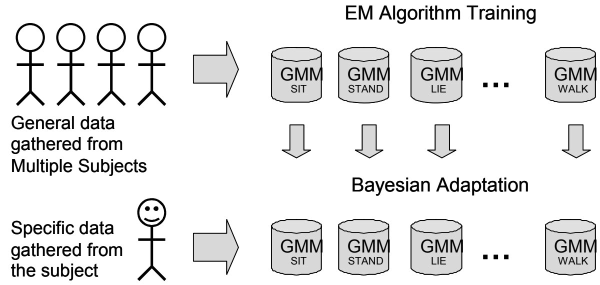

Fig. 4. Proposed adaptation method. The GMMs are first trained on data from multiple subjects using the EM algorithm and then adapted to a specific subject using Bayesian adaptation.

Similarly to the method used in [11] for speaker verification, the means of the ith GMM mixture component $\hat{\mu}_i$ are adapted from there previous values μ_i over successive iterations according to [11]:

$$\hat{\mu}_i = \alpha_i E_i(X) + (1-\alpha_i)\mu_i$$

where γ is a scaling factor used to ensure that the adapted weights sum to unity,

$$E_i(X) = \frac{1}{n_i}\sum_{t=1}^{T} P(i \mid x_t, \lambda) x_t,$$

and $$\alpha_i = \frac{\sum_{t=1}^{T} P(i \mid \vec{x}_t, \lambda)}{r + \sum_{t=1}^{T} P(i \mid \vec{x}, \lambda)}$$

where $$P(i \mid \vec{x}_t, \lambda) = \frac{w_i b_i(\vec{x}_t)}{\sum_{k=1}^{K} w_k b_k(\vec{x}_t)}, \quad (9)$$

λ is the parameterization of the GMM on the previous iteration and r (=2 or 4) is a fixed relevance parameter.

III. Results and Discussion

A. Front-end Features Comparisons

Experiments were performed comparing the time-domain features with the frequency domain features. Results are given in Table 1. The proposed time domain features performed better than the frequency domain features, particularly in the identification of the short-duration transitions between standing and sitting/lying. Overall, they give a relative improvement in error rate of 39.2% over the FFT-based features.

Due to the use of only a single waist-mounted device, reduced ability to distinguish between sitting and standing is evident for both feature types. However the ability of the time-domain features to accurately identify both types of transition between sitting and standing should allow improved discrimination between sitting and standing via a simple heuristic overlay or Markov chain.

TABLE 1. COMPARISON OF TIME AND FREQUENCY DOMAIN FEATURES. RESULTS ARE MEAN ACCURACY AND STANDARD DEVIATIONS ACROSS THE SIX HUMAN TRIAL SUBJECTS.

Classification		Mean Accuracy (%)	
		Time Domain Features	FFT-based Features
Postures	Sitting	79.2	70.4
	Standing	77.3	80.9
	Lying	91.4	88.1
Movements	Stand-to-Sit	93.1	81.6
	Sit-to-Stand	88.3	78.3
	Stand-to-Lie	98.5	93.8
	Lie-to-Stand	98.9	92.7
	Walking	97.8	97.9
Overall		**91.3**	**85.7**

B. Subject Specific Adaptation

Tests were performed to assess the effectiveness of the adaptation technique on both time and frequency based features. For each of the six subjects, results were obtained for GMMs trained using data from only that subject, combined data from the other five subjects, and combined data from the other five subjects adapted using data specific to that subject. Results are shown in Table 2.

TABLE 2. RESULTS OF EXPERIMENTS DEMONSTRATING THE EFFECTIVENESS OF THE PROPOSED ADAPTATION TECHNIQUE.

Training Scheme	Mean Accuracy (%)	
	Time Domain Features	FFT-based Features
Same subject training	88.2	**85.1**
Other subject training	76.6	71.3
Other subject training + Same subject adaptation	**92.2**	79.2

For the time domain features, the adaptation technique was found to offer improved results over both the subject specific only and non subject-specific training with relative improvements in error rate of 4.5% and 20.2% respectively. For the frequency based features, the adaptation did not perform as well, being outperformed by the subject specific training in all cases but still offering a relative reduction in error rate of 42.8% over non subject-specific training. One possible explanation is that the frequency domain features are more subject-specific than the time-domain features.

IV. CONCLUSION

An investigation has been conducted into the effectiveness of using time and frequency domain features for classification of human movement from accelerometry data. This work demonstrated that using a single triaxial accelerometer attached at the waist, a series of basic postures and motions can be more accurately identified using the proposed time-domain features than by previously used frequency domain features. A method for adapting GMM parameters to better fit the movements of a particular individual was also further investigated. Compensating for a lack of recipient-specific training data, this method was found to achieve improvements in accuracy when applied using the proposed time domain features.

Future work will investigate the extension of these methods to other movement categories and look to applying them in a practical real-time system.

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